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Predictive Closed-loop Control of Musculotendon Force: Towards a Framework for Human Locomotion*

Mahdi Nabipour[1], Gregory S. Sawicki[2], *Member, IEEE,* and Massimo Sartori[1], *Member, IEEE*

Abstract— **Exosuits and exoskeletons show promise in aiding locomotion for both healthy and pathological populations. However, the impact of exosuit assistance on the underlying muscle-tendon loading remains unclear. In this study, our objective is to gain control over the mechanics of biological tissues, offering avenues for preventing musculoskeletal injuries and tailoring rehabilitation treatments with unprecedented precision. To achieve this goal, we introduce a novel framework utilizing Nonlinear Model Predictive Control (NMPC) for closed-loop control of Achilles tendon force during simulated human ankle joint motion with parallel exoskeletal actuation. The proposed NMPC framework integrates a computationally efficient inner model consisting of explicit, closed-form Ordinary Differential Equations (ODEs) governing muscle-tendon dynamics and ankle joint behavior with parallel actuation. We assess the controller's performance through hopping simulations, varying muscle excitation amplitude and frequencies. Furthermore, we extend the model to enable the use of the same control framework for musculotendon unit (MTU) force control in walking scenarios. The results confirm the versatility of our proposed model across different muscles and gait patterns, demonstrating its suitability for real-time applications due to its low computational time.**

I. Introduction

The development of wearable technologies providing adaptive mechanical assistance to biological tissues and joints remains a significant ongoing challenge. Researchers have introduced human-in-the-loop (HIL) optimization methods to address this challenge. These methods aim to optimize the assistive torque profiles for the active exoskeletons, to minimize an individual's metabolic energy consumption during gait [1]. The assistive torque profile parameters are specified in an iterative approach using evolutionary algorithms. As a consequence, the current state-of-the-art HIL optimization approaches are time-consuming, often requiring several minutes to converge to an optimal torque profile [2]. This extended duration raises concerns about the practicality and real-time applicability of these methods in dynamic, everyday scenarios [3]. Future advancements in this field may prioritize enhancing the efficiency and speed of HIL optimization techniques, ensuring their feasibility for real-world use, and promoting the widespread adoption of wearable robotic exoskeletons.

State-of-the-art advancements in lower limb exoskeletons' control prioritize the reduction of walking metabolic costs but cannot often control biological tissue mechanics. Recent studies have underscored the significance of exploring changes in Achilles tendon force when utilizing exosuits. One such study employed nine predefined plantarflexion assistance profiles to modulate Achilles tendon force effectively [4]. Another study designed the exosuit assistance profile to be proportional to the estimated Soleus muscle force [5]. In this paper, we seek to address this gap by developing a robotic assistance methodology for controlling the biological musculotendon force in an assist-as-needed (AAN) fashion. By doing so, we would be able to prevent musculoskeletal injuries as well as optimize the rehabilitation process for the injured tissue. Specifically, our focus is on predicting and controlling peak Achilles tendon force during cyclic motions, e.g., hopping and walking, which necessitates a novel class of millisecond-operating controllers. These controllers aim to rapidly determine optimal torque profiles, preventing tendon torque from exceeding predefined thresholds.

To address this challenge, our proposed solution involves utilizing a prediction of biological tendon force estimates to control wearable devices. Our approach centers on developing novel combined closed-form models for the human-exoskeleton system, establishing relations between their respective states. For real-time predictions of the important variables inside the prediction horizon, this model needs to be computationally efficient. To do this, we apply the MPC methodology, minimizing a cost function throughout the course of the prediction horizon while tolerating constraints. While MPC has previously found application in generating assistive device joint torques [5] and optimal joint trajectories [6], its utilization for the control of muscle-tendon mechanics is novel. This new approach has the potential to achieve precise control over peak tendon force, representing a significant breakthrough in exoskeleton technology and human-machine interface.

The musculotendon units (MTUs) can be numerically modeled to simulate both the mechanics of series elastic tendons and muscle contraction. This numerical representation enables the estimation of time profiles for biomechanical variables that may be challenging or impossible to measure directly in intact, moving humans in vivo [7]. Hill-type models [8], which need fewer parameters than alternatives like Huxley's muscle contraction models [9], [10], are often used to model MTU dynamics. Many mathematical formulations

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[1]Mahdi Nabipour and Massimo Sartori are with the Neuromechanical Modeling and Engineering Laboratory, Department of Biomechanical Engineering, University of Twente, 7522 NB Enschede, The Netherlands m.sartori@utwente.nl.

[2]Gregory S. Sawicki is with the Human Physiology of Wearable Robotics (PoWeR) laboratory, School of Mechanical Engineering, Georgia Institute of Technology North Avenue Atlanta, GA 30332 gregory.sawicki@me.gatech.edu.

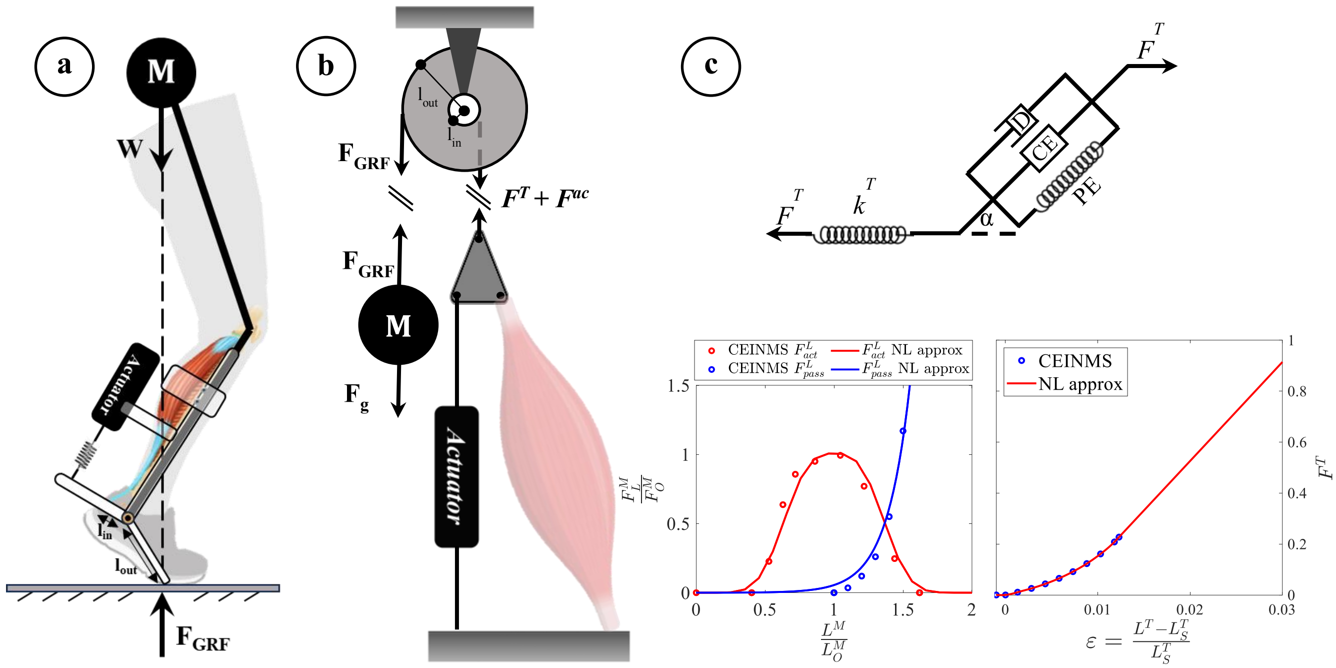

Figure 1. The models used for hopping. a) The actual model of the combined system, (b) The simplified model of the combined system, (c) damped Hill-type muscle model, the active/passive force-length relation, as well as the tendon strain-stiffness relation

available in the literature employ non-linear splines for interpolating empirically collected data that represent relationships among muscle force, length, velocity, tendon force, and strain. These formulations are commonly utilized to characterize Hill-type muscle contraction and tendon strain mechanics. However, existing formulations often resort to conditional statements rather than yielding closed-form equations [8], [11], [12], suitable for being used within the NMPC framework. When integrating these formulations into control theory frameworks and employing MPC methods, the reliance on conditional assertions introduces challenges and complexities. A regression-based closed-form formulation for the damped Hill-type muscle model was presented in [13]. After comparing the suggested approach to a formulation derived by linearizing the muscle Force-Velocity (F-V) [14], it was seen that the latter model exhibits broader applicability across various muscles and walking/running speeds.

In this paper, our initial focus is on introducing a closed-form Hill-type MTU model and seamlessly integrating it into a simplified hopping model, outlined in [15], [16]. This model is further enhanced with a parallel assistive device, chosen among various possible exoskeleton designs [17]. Subsequently, we present a control framework designed to predict future MTU force within a specified horizon and provide assistance to the muscle when it surpasses a predefined threshold. To assess the efficacy of this assist-as-needed framework, we analyze the results obtained by applying this controller to simulated hopping scenarios. Furthermore, we explore the feasibility of employing the same control structure for walking across various speed scenarios using a modified version of the Spring-Loaded Inverted Pendulum (SLIP) model.

II. Methods

In this section, a comprehensive exploration of the modeling and control of the integrated human-exoskeleton system is provided. Initially, the modeling approach employed to derive the closed-form model of the Hill-type muscle is presented. Subsequently, the methodology for seamlessly combining this muscle model with an exoskeleton during both hopping and walking activities is presented.

A. Modeling the MTU

We employ a damped pennate Hill-type muscle model, (Fig. 1-c), to describe the dynamics of the MTU contraction [18], [19]. This form of muscle model consists of a contractile element in combination with series and parallel elastic elements. The governing ordinary differential equation (ODE) for the tendon force in a pennate Hill-type muscle model is as follows [20]:

$$\dot{F}^T = k^T\left(\dot{L}^{MT} - \dot{L}^M\cos(\alpha) + L^M\dot{\alpha}\sin(\alpha)\right) \tag{1}$$

where α denotes the muscle's pennation angle in this equation. The tendon force and stiffness are denoted by F^T and k^T, while the muscle fiber and MTU lengths are indicated by L^M and L^{MT}, respectively. k^T and other MTU parameters are obtained by calibrating the model for each subject. L^{MT} and its derivative are obtained by the kinematics of the motion. $\dot{L}^M$ is the most challenging part of the equation to derive the damped Hill-type muscle model's governing closed-form equation.

To overcome this challenge, we can take advantage of the fact that the normalized velocities of lower limb eccentric and concentric contractions often remain within the range of ±0.5 [19] during activities such as walking and running. The F-V relationship used in the CEINMS toolbox, as shown in Fig. 2, is almost linear in the ±0.5 normalized velocity range. Thus, in this particular velocity range, we can approximate the almost exponential behavior of the muscle as linear. Based on this presumption, $F^V = F_O^M(k_1\dot{\tilde{L}}^M + k_2)$,the tendon force of the damped Hill-type muscle model is obtained as:

$$\frac{F^T}{\cos(\alpha)} = F_O^M \cdot \left(a(t).\tilde{F}_L^M \left(k_1 \dot{\tilde{L}}^M + k_2\right) + \tilde{F}^{PE} + b\dot{\tilde{L}}^M\right) \quad (2)$$

where *a(t)* is the muscle activation and F_O^M, $\tilde{F}^{PE}$, and $\tilde{F}_L^M$ represent the maximum isometric force, normalized active force-length relation, and the normalized parallel elastic element force, respectively. Also, k_1 and k_2 denote the parameters of the linear approximation used to model the F-V relation within the range of ±0.5 and *b* represents the Hill-type muscle damping.

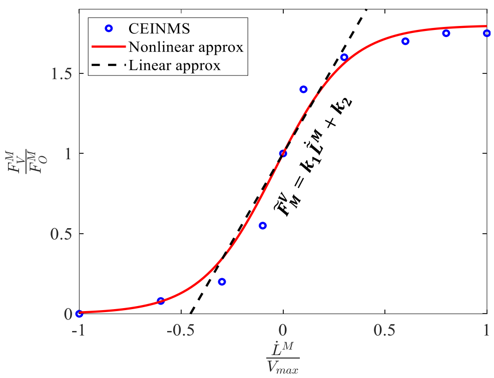

Figure 2. The force-velocity relation data used in CEINMS and its linear/nonlinear approximation.

Therefore, by rearranging equation (2), the only unknown parameter of equation (1), muscle fiber velocity, can be obtained as follows:

$$\dot{L}^M = V^{\max}\left(\frac{\dfrac{F^T}{\cos(\alpha)} - \tilde{F}^{PE} - a(t).F_O^M \tilde{F}_L^M k_2}{F_O^M\left(a.\tilde{F}_L^M.k_1 + b\right)}\right) \quad (3)$$

where V^{max} is the maximum shortening velocity of muscle fiber and α is the pennation angle. Equation (1) should be combined with a motion related (e.g., hopping or walking in our case) equation to form NMPC framework's inner model.

B. *Simplified hopping dynamics*

Incorporating an additional equation linking tendon force to the intended movement is crucial for the model-based control of the MTU force. Robertson et al. [15] introduced a simplified pulley-mass model of the human leg that captures the key aspects of rhythmic locomotion, especially for hopping. In their proposed model, the triceps surae is represented by a non-pennated Hill-type muscle without parallel damping. To integrate this model into an exoskeleton-MTU combined model, a parallel actuator is introduced (depicted in Fig. 1-a,b). The governing equations for this combined model are as:

$$\begin{aligned} \dot{F}^T &= k^T\left(\dot{L}^{MT} - \dot{L}^M\cos(\alpha) + L^M\dot{\alpha}\sin(\alpha)\right) \\ \ddot{L}^{MT} &= -\frac{g}{W}\left(F^T + F^{ac} - W\right) \end{aligned} \quad (4)$$

The rate of change of the lumped triceps surae MTU velocity is dictated by the motion. Since hopping is a symmetric motion, half of the weight *W* is carried by each leg. Also, the assistive actuator force, F^{ac} (Figure 1-a,b), is provided by the ankle exoskeleton. With the equations derived, the combined model is now a nonlinear state space model of the combined human-exoskeleton system during hopping

$$\dot{x} = f\left(x,u,a(t)\right),\; x = \left[F^T \quad L^{MT} \quad \dot{L}^{MT}\right]^T,\; u = F^{ac} \quad (5)$$

This model is well-suited for the design of various linear and nonlinear model-based controllers. It is important to note that the superscript *T* over the bracket of the state vector, *x*, represents the transpose.

C. *Towards modeling walking*

Similar to hopping, to effectively control MTU force during walking across various speeds, a model is essential to establish a connection between the motion and MTU force. In mid- to late-stance phase of walking, a predominant portion of the joint torque is attributed to the plantarflexors. Notably, the peak force experienced by the Achilles tendon occurs within this phase of the gait cycle, making it a critical interval for MTU force control. During this segment of the gait, the center of pressure (COP) exhibits minimal displacement, and the center of mass (COM) traverses over the COP.

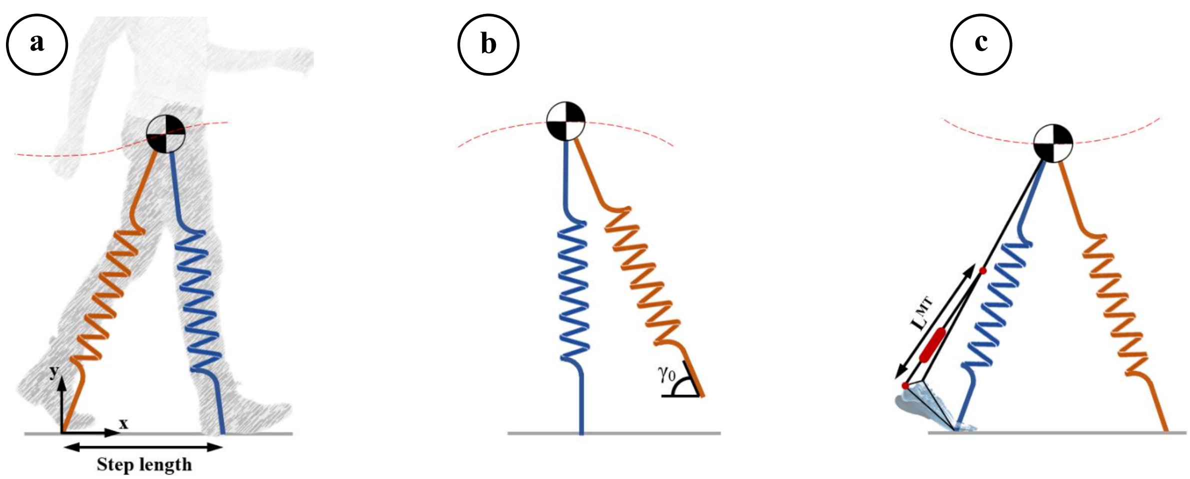

Figure 3. The modified SLIP model used for specifying the trajectory of the COM during walking a) with constant step length and b) with constant heel contact angle. c) By adding lumped triceps surae muscle to the SLIP model, the combined model is ready for being utilized in control. The MTU length changes as the ankle joint rotates during mid- to late-stance.

The model introduced here for the first time, is a modified version of the SLIP model introduced in [21], consisting of the lumped plantarflexors attached to the calcaneus and the knee joint, a point mass *m*, positioned atop a massless, springy leg characterized by a rest length L_0 and a spring constant k. The configuration of the system is determined by the position of the center of mass, denoted by (x_{COM}, y_{COM}), along with the length L_0 and heel contact angle γ_0 of the leg. The dynamics of the system are segmented into two distinct phases: the single support phase (SSP) and the double support phase (DSP), each governed by separate sets of equations. During the flight phase, one set of dynamics is in effect, while a different set of equations governs the system's behavior during the stance phase.

D. *Predictive controller framework*

The control framework (Fig. 2) is designed to control MTU forces in the lower limbs during hopping with different frequencies, walking at varying speeds, and has the potential for extension to address MTU forces in the trunk/upper limb. This control framework comprises three key components: a) the tendon force predictor, b) desired force estimator, and the NMPC algorithm (for more information, refer to [22]).

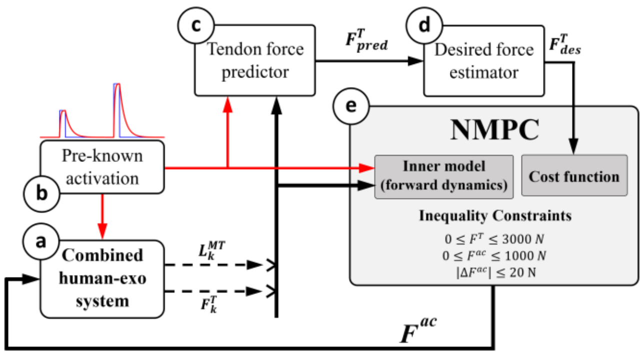

Figure 4. NMPC framework: Closed-form dynamics of the combined MTU and motion-related ODEs use pre-known activation (b) to generate MTU force in the human-exo system (a) and tendon force predictor (c). The predicted tendon force is used to obtain the desired tendon force (d), which is transferred to the NMPC (e) with the activation and current MTU length and force.

Both the tendon force predictor and the NMPC controller employ the model derived from the preceding sections to predict future tendon force (for the predictor) and function as an internal model within the NMPC. The optimization of the assistance value is achieved using the following cost function:

$$J = \sum_{k=1}^{horizon} w_1 \left(F^{ac}\right)^2 + w_2 \left(\Delta F^{ac}\right)^2 + w_3 \left(F^T{}_k - F^T{}_{des}\right)^2 \quad (6)$$

where w_i are constants and specify the impact of tendon force, the actuator force F^{ac}, and its increment on the value of the cost function. This cost function is minimized over the entire control horizon. In this paper, we assume that the muscle activation is known beforehand, which is deemed reasonable, especially when using muscle synergies for repetitive motions. As such, we use this pre-known activation as input for the forward dynamics model integrated into the tendon force predictor and the inner model of the controller, as well as the human muscle model. In addition to the closed-form model of the combined human-exoskeleton system, some other constraints are considered for the maximum MTU force and the actuator (as depicted in Fig. 4).

The prediction of future tendon force occurs within the initial control horizon, configured for a duration of 100ms. Following the estimation of the predicted tendon force, the system identifies the maximum value and the corresponding time of occurrence. If the determined time of occurrence is found to be less than 100ms, that specific moment is designated as the new control horizon. The controller is activated when the predicted maximum tendon force exceeds the predefined tendon force threshold (3000N). The desired tendon force profile over the control horizon is the value of the predicted tendon force when below the threshold and equal to the threshold when the predicted force is above the threshold.

III. Results and Discussions

A. *Modeling the combined MTU-exoskeleton system*

One of the significance of the method of linearizing F-V relation, in comparison to the regression method presented in [14], lies in the absence of the need of individual muscle optimization. Moreover, the incorporation of damping in the Hill-type muscle model enhances stability; the muscle does not diverge even when the muscle activation approaches zero. This stability contrasts with scenarios where damping is not utilized or when employing the regression method [13].

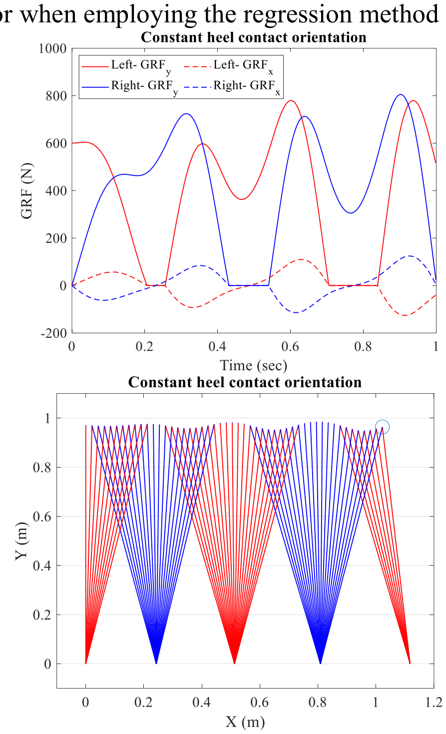

Figure 5. GRF, COM trajectory, and step locations when using constant heel contact orientation.

As illustrated in both locomotion models featuring a consistent heel contact orientation (Fig. 5) and the SLIP model maintaining a constant step length (Fig. 6), the ground reaction forces (GRFs) generated by these models result in walking. The results indicate that the model using a constant step length yields more stable solutions, converging to the limit cycle at least one step duration faster than the model with a fixed heel contact orientation. This suggests that it is more reliable for use in NMPC to predict the future center of mass trajectory, as it adapts to the appropriate step length for each walking velocity. However, the model with a fixed heel contact orientation should also be explored in future studies. We can specify different system energies, E_s, for regulating the speed of walking in the SLIP model. In the case of using stiffness of $k = 20 \times 10^3$ N/m for the stance leg, $L_0 = 1$ m, the apex height of 0.97 m, and $\gamma_0 = 76^o$ the step lengths of the constant heel contact angle model will be about 25 cm. For having a 65 cm step length, the stiffness of $k = 14 \times 10^3$ and $\gamma_0 = 64^o$ should be used.

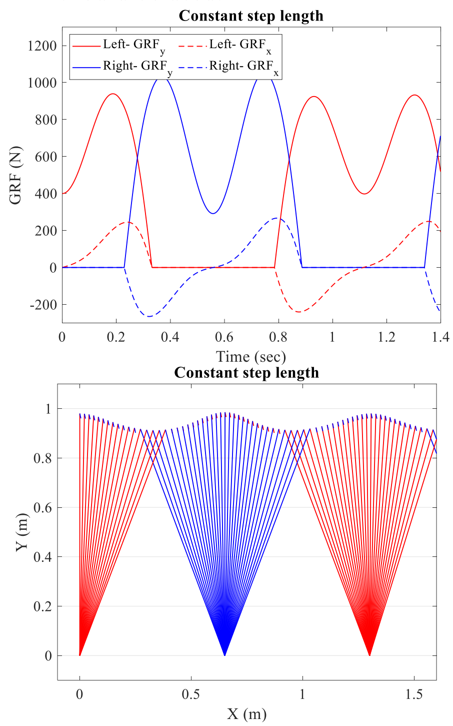

Figure 6. GRF, COM trajectory, and step locations when usin constant step length for the SLIP model

B. *NMPC performance*

To assess the performance of the predictive control structure, a series of simulations were conducted for the hopping scenario. We investigated how the coupled system of a human-exoskeleton device responded to varying frequencies and magnitudes of muscle excitation during simulated hopping. This motion heavily depends on the ankle MTUs, particularly the triceps surae Achilles tendon complex, accounting for a substantial portion (up to 80%) of the limb's total positive mechanical power to meet the mechanical work requirements of the task [16]. Hence, for the purpose of evaluating the performance of the NMPC in different hopping scenarios, the muscle undergoes excitations ranging from 0.05 magnitude to 1 with increment of 0.05. Additionally, the muscle excitation period experiences various values, ranging from 0.25 s (corresponding to a frequency of 4 Hz) to 1 s (corresponding to a frequency of 1Hz), with increment of 50 ms.

The controller's objective is to keep the Achilles tendon force under 3000 N. For the NMPC controller, the initial horizon was chosen to be 100ms and it decreased as the force in the tendon gets closer to the threshold. The minimum value for the horizon was selected as 50 ms. The investigation involved testing various zero-order-hold (ZOH) values, revealing that an interior point optimizer could solve this direct collocation optimization problem on system with 16 GB RAM and an Intel(R) Core(TM) i7-11800H @ 2.30GHz in 14 ms maximum, when employing a ZOH of 10. This time frame falls well within the range of the physiological electromechanical delay.

Fig. 7 illustrates the effectiveness of NMPC in maintaining the tendon force below the 3000 N threshold. The contour plots depict the maximum tendon force values at each period and amplitude of muscle excitation. In these plots, the x-axis represents the period in milliseconds, and the y-axis represents the amplitudes of muscle excitation. When the user undergoes different excitation periods and amplitudes, the maximum tendon force without any assistance is plotted in the Fig. 7-a. The parts of the figure which are in green, are those that the Achilles tendon force is maintained under 3000N. The parts in yellow show the regions of excitation and period that the tendon force surpasses the threshold. As

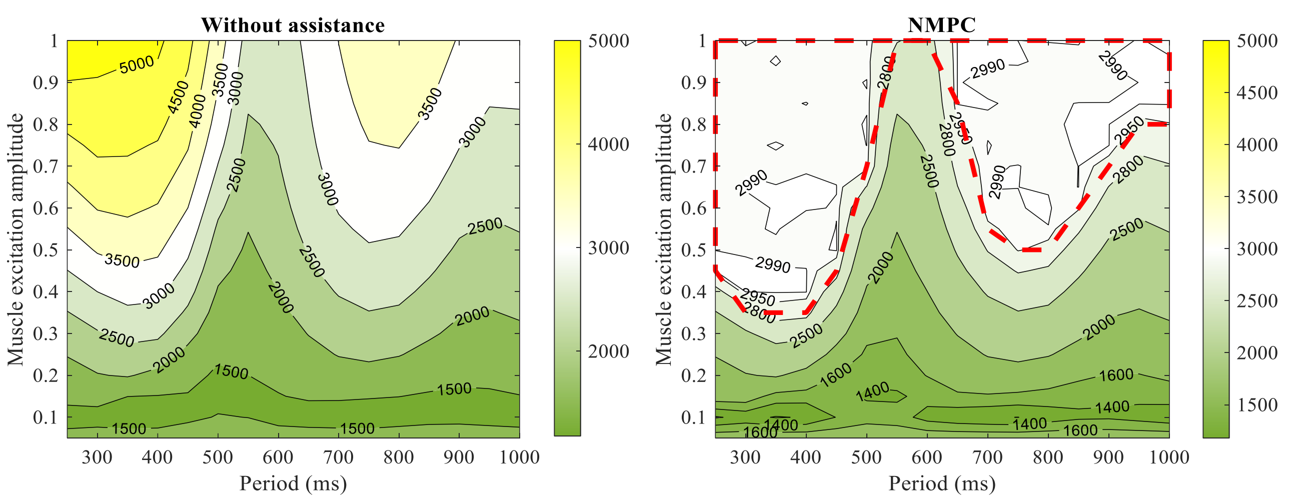

Figure 7. The maximum tendon forces when changing the muscle excitation amplitude and period when no exoskeleton assistance is used and when the NMPC is used for controlling the exoskeleton. The values in the contours are in newtons.

depicted in Fig. 7-b, the tendon force consistently remains below the threshold when employing NMPC. The dashed red lines represent the range within which the force predictor of the controller predicts that the tendon force is likely to surpass the threshold in the future. In such instances, the controller is activated preemptively to provide assistance and prevent the force from exceeding the established limit. As depicted, when the controller is active, the tendon force consistently hovers within the range of 2800 to 2990 N. The proximity of this value to the threshold contributes to user comfort during the assistance phase.

C. Future work

In the future, the designed NMPC approach will be tested on healthy subjects during hopping. In addition, given that the modified SLIP model is applicable during the mid- to late-stance phase of gait, particularly when the plantarflexors exert dominance over the dorsiflexors, and considering that the maximum Achilles tendon force occurs within this phase of the gait cycle, NMPC will be implemented to regulate the MTU force during walking within this specific timeframe.

IV. Conclusion

In conclusion, this paper introduced an innovative framework for the closed-loop control of peak tendon force in a simulated human ankle joint system with parallel exoskeletal actuation. By employing nonlinear model predictive control (NMPC) in conjunction with a computationally efficient inner model governed by explicit, closed-form ordinary differential equations (ODE), we make a substantial stride in filling the existing gap in the control of biological tissue mechanics within the realm of robotic exoskeletons.

Our approach integrates a set of explicit, closed-form, differentiable equations for a Hill-type musculotendinous unit (MTU) system with parallel damping, along with the equation of motion for the human leg with parallel exoskeletal actuation, all encapsulated within the NMPC framework for the first time. The outcomes highlight the effectiveness of our proposed control framework, successfully maintaining tendon force below a predetermined threshold across diverse simulated conditions, including hopping with varying muscle excitation amplitudes and frequencies.

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